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# Forecasting Precious Metal Prices Using Simulated Data: A Comparative Study Using MLP, ARIMA and SVR

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**Abstract:** Forecasting of precious metal prices accurately is of crucial importance of an informed financial decision-making, robust risk mitigation and strategic asset allocation. This study represents a comparative analysis of time series forecasting methodologies including — Autoregressive Integrated Moving Average (ARIMA), Multilayer Perceptron (MLP), and Support Vector Regression (SVR) applied to the monthly historical datasets of gold and silver prices. These datasets were generated using OpenAI's ChatGPT for academic purposes. These datasets are simulated and do not directly reflect real-world market data unless otherwise data is validated. Each of the models is evaluated over a 24-month out-of-sample forecasting horizon using rigorous statistical metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The empirical findings underscore the comparative advantages of data-driven machine learning approaches, particularly in capturing nonlinear and volatile dynamics, with MLP and SVR outperforming ARIMA in most scenarios. These results emphasize the increasing relevance of advanced machine learning techniques in financial time series modelling.

**Keywords:** Simulated Data, Comparative Study, Metal, MLP, ARIMA, SVR, Time Series, forecasting

## I. Introduction

The predictive modelling of precious metal prices, specifically those of gold and silver, plays a very important role in financial analysis because of their intrinsic value, function as hedging instruments, and sensitivity to macroeconomic fluctuations. These asset classes are subject to a multitude of exogenous variables, including global monetary policies, inflationary trends, currency exchange volatility, and geopolitical developments. Their inherently non-stationary and nonlinear behaviors present significant methodological challenges for forecasters.

Traditional econometric approaches, such as the Autoregressive Integrated Moving Average (ARIMA) model, have served as foundational tools in time series forecasting, primarily because of their interpretability and effectiveness in modeling linear temporal dependencies. However, their capacity to address structural breaks and nonlinearities is limited, rendering them less effective in turbulent or highly dynamic market environments.

Recent advancements in computational intelligence have introduced powerful machine learning algorithms can uncover complex patterns in financial time series. Neural networks, especially Multilayer Perceptron's (MLPs), have demonstrated the ability to model long-range dependencies and intricate nonlinear relationships. Similarly, Support Vector Regression (SVR) offers strong generalization performance, particularly in high-dimensional and small-sample scenarios, making it a valuable tool for financial forecasting. Scientifically compare the forecasting efficacy of ARIMA, MLP, and SVR models is the main aim of this study when applied to gold and silver price series. Through rigorous experimentation and quantitative evaluation using RMSE, MAE, and MAPE, the objective is to identify the relative strengths and limitations of each modeling paradigm, ultimately contributing to more deep intelligence tools in the domain of financial econometrics.

## II. Methodology

The analytical framework involves the deployment of ARIMA, MLP, and SVR models on monthly historical price data of gold and silver. Data preprocessing constitutes the initial phase, encompassing the imputation of missing values through interpolation techniques and transformation of the series to achieve stationarity. Stationarity is verified via the Augmented Dickey-Fuller (ADF) test, and model specification for ARIMA is guided by Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) diagnostics. The dataset is partitioned into training and test subsets in an 80:20 ratio, with a forecast horizon spanning 24 months.

The ARIMA model is parameterized using the auto. Arima () function from R's forecast package, which selects optimal (p, d, q) values by minimizing the Akaike Information Criterion (AIC). Differencing is applied where necessary, and residual diagnostics—including the Ljung-Box test—are conducted to assess model adequacy. For linear modelling performance ARIMA serves as a benchmark.

For the MLP model, implemented via the Keras or nnet packages in R, the time series was normalized using Min-Max scaling to facilitate neural learning. The lagged observations were structured in a supervised learning format. The Model architecture, including the number of hidden layers and neurons, was iteratively tuned. Techniques such as early stopping and dropout were employed to mitigate over fitting. After prediction, outputs were rescaled to the original price range.

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The SVR model was constructed using the e1071 or kernlab packages. Similar to MLP, lag-based feature engineering and normalization are applied. A sliding window framework generates training sequences. Hyper parameter tuning for cost (C), epsilon (ε), and kernel function (typically radial basis function) is performed via cross-validation. Particularly for nonlinear regression tasks SVRs performs well by maintaining equilibrium between over fitting and generalization.

The forecast performance was assessed using RMSE, MAE, and MAPE. Visualizations accompany the forecasted outputs, juxtaposed against historical observations, and include 95% confidence intervals to enhance interpretability.

In this study, the performance of the ARIMA, MLP, and SVR models is assessed using three commonly employed accuracy metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics help evaluate the accuracy and reliability of the forecasted values compared to the actual observed prices of gold and silver over a 24-month forecast period.

**Accuracy measures:**

**Root Mean Square Error (RMSE):**

RMSE indicates how large the prediction errors are, on average, by taking the square root of the average squared differences between the forecasted and true values. The lower the RMSE, the better the model's predictions are aligned with the actual data.

Mathematically, it is expressed as:

**Mean Absolute Error (MAE):**

MAE represents the average of the absolute differences between predicted and actual values, offering a simple metric for predicting the error. It is easier to interpret than RMSE as it measures the average magnitude of errors without considering their direction (positive or negative). I

**Mean Absolute Percentage Error (MAPE):**

MAPE provides a percentage measure of prediction accuracy, which is useful for comparing forecasting performance across different datasets or models. It is the mean of the absolute percentage error between the actual and predicted values:

A lower MAPE indicates a higher degree of accuracy in the model's forecasts.

These three metrics were selected for their ability to capture different aspects of model performance: RMSE is sensitive to larger errors, MAE provides a more straightforward error measurement, and MAPE offers a normalized error measurement in percentage terms. By comparing these metrics across the ARIMA, MLP, and SVR models, we can comprehensively evaluate the relative strengths and weaknesses of each method in forecasting precious metal prices

**III. Result and Discussion**

A comparative performance analysis of the ARIMA, MLP, and SVR models revealed distinct strengths across various forecast horizons and data behaviors. All models were trained on 80% of the dataset and tested on the remaining 20% under identical pre-processing conditions.

The ARIMA model demonstrated satisfactory performance in modeling linear patterns and seasonality, particularly when the series was properly differenced to attain stationarity. However, it exhibited diminished accuracy during periods of abrupt market shifts, suggesting its limitations in modeling nonlinear phenomena.

In contrast, the MLP model, once optimally tuned, displayed superior performance in both the training and test sets, particularly in terms of RMSE and MAE. Its ability to capture higher-order dependencies and complex temporal dynamics allows it to effectively model both short-term fluctuations and long-term trends. Notably, MLP maintained robust performance during volatile market phases, highlighting its adaptability.

The SVR model also yielded competitive results. Its kernel-based approach allowed for effective nonlinear approximation with minimal over fitting. Although its training error was occasionally higher than that of MLP, SVR consistently outperformed ARIMA across all evaluation metrics. It was particularly adept at modeling moderate nonlinearities and exhibits high stability across varying market regimes.

Graphical comparisons further validate the numerical findings. ARIMA forecasts appeared smoothed and occasionally lagged rapid price transitions. Conversely, MLP and SVR forecasts more accurately mirrored the dynamic structure of the underlying series. The confidence intervals for MLP and SVR forecasts were narrower, indicating higher model confidence and reduced variance.

These outcomes substantiate the hypothesis that machine learning models, particularly neural networks, and support vector-based approaches, offer distinct advantages over traditional statistical techniques in modeling financial time series characterized by volatility and nonlinearity.

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**Table 1** Performance Evaluation Table: Comparison of ARIMA, MLP and SVR Model:

| Commodity | | ARIMA | MLP | SVR |
|---|---|---|---|---|
| GOLD | RMSE | **59.55782** | 660.8597 | 215.05 |
| | MAE | **43.34726** | 551.5852 | 178.70 |
| | MAPE | **3.738392** | 21.5629 | 9.18 |
| SILVER | RMSE | **1.93955** | 6.917 | 9.15 |
| | MAE | **1.242198** | 5.606 | 8.13 |
| | MAPE | **6.613593** | 18.76 | 31.26 |

The significance of the "bold" is indicated as smallest value.

**Table 2** Forecasting using the ARIMA Model for Gold: The Forecasted Values for year 2025 and 2026 are as follows:

| Month | Forecast | Lower Bound (95%) | Upper Bound (95%) | Month | Forecast | Lower Bound (95%) | Upper Bound (95%) |
|---|---|---|---|---|---|---|---|
| **Apr-25** | 3017.566 | 2900.239 | 3134.894 | **Apr-26** | 3128.667 | 2738.879 | 3518.456 |
| **May-25** | 3026.825 | 2867.828 | 3185.821 | **May-26** | 3137.925 | 2733.637 | 3542.214 |
| **Jun-25** | 3036.083 | 2844.266 | 3227.9 | **Jun-26** | 3147.184 | 2728.898 | 3565.47 |
| **Jul-25** | 3045.341 | 2825.551 | 3265.132 | **Jul-26** | 3156.442 | 2724.612 | 3588.273 |
| **Aug-25** | 3054.6 | 2810.014 | 3299.186 | **Aug-26** | 3165.701 | 2720.738 | 3610.663 |
| **Sep-25** | 3063.858 | 2796.77 | 3330.947 | **Sep-26** | 3174.959 | 2717.241 | 3632.677 |
| **Oct-25** | 3073.117 | 2785.279 | 3360.954 | **Oct-26** | 3184.217 | 2714.09 | 3654.345 |
| **Nov-25** | 3082.375 | 2775.187 | 3389.563 | **Nov-26** | 3193.476 | 2711.258 | 3675.693 |
| **Dec-25** | 3091.633 | 2766.244 | 3417.023 | **Dec-26** | 3202.734 | 2708.722 | 3696.746 |
| **Jan-26** | 3100.892 | 2758.266 | 3443.518 | **Jan-27** | 3211.993 | 2706.461 | 3717.524 |
| **Feb-26** | 3110.15 | 2751.114 | 3469.186 | **Feb-27** | 3221.251 | 2704.457 | 3738.045 |
| **Mar-26** | 3119.409 | 2744.681 | 3494.136 | **Mar-27** | 3230.509 | 2702.693 | 3758.326 |

Table represents forecast with 95% confidence interval for Gold.

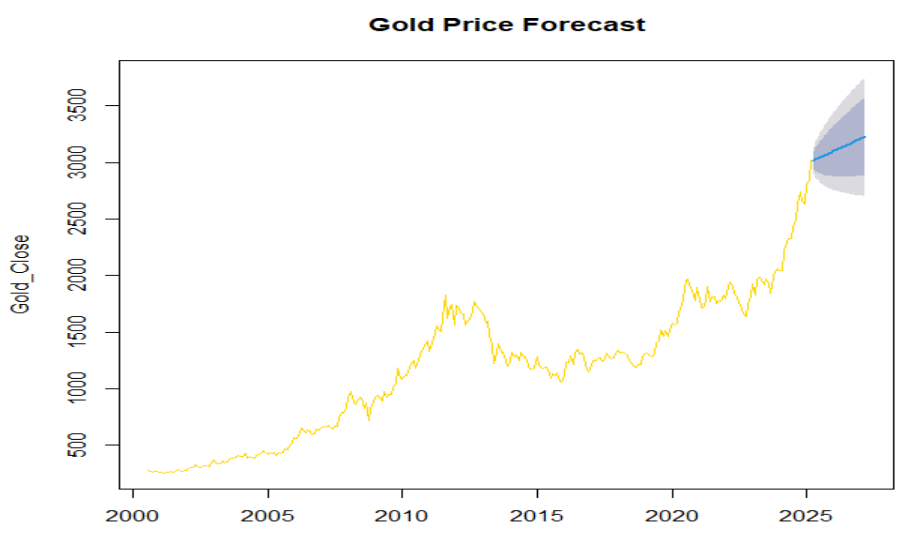


Fig.1. Forecast -plot using 95% confidence interval for Gold.

**Table 3 Forecasting using ARIMA Model for Silver:** The Forecasted Values for years 2025 and 2026 are as follows

| Month | Forecast | Lower Bound (95%) | Upper Bound (95%) | Month | Forecast | Lower Bound (95%) | Upper Bound (95%) |
|---|---|---|---|---|---|---|---|
| **Apr-25** | 33.95266 | 30.1981 | 37.70722 | **Apr-26** | 33.54044 | 21.97167 | 45.10921 |
| **May-25** | 33.73406 | 28.65191 | 38.81621 | **May-26** | 33.81972 | 21.85504 | 45.7844 |
| **Jun-25** | 33.39379 | 27.4625 | 39.32472 | **Jun-26** | 33.61078 | 21.21559 | 46.00597 |
| **Jul-25** | 34.05733 | 27.4059 | 40.70887 | **Jul-26** | 33.67836 | 20.91101 | 46.4457 |
| **Aug-25** | 33.39342 | 25.9324 | 40.85411 | **Aug-26** | 33.75398 | 20.60121 | 46.90676 |
| **Sep-25** | 33.79215 | 25.7899 | 41.79441 | **Sep-26** | 33.5909 | 20.06287 | 47.11893 |
| **Oct-25** | 33.77081 | 25.12185 | 42.41976 | **Oct-26** | 33.76065 | 19.88719 | 47.63412 |
| **Nov-25** | 33.47345 | 24.27585 | 42.67105 | **Nov-26** | 33.6533 | 19.41594 | 47.89065 |
| **Dec-25** | 33.91384 | 24.23087 | 43.59681 | **Dec-26** | 33.66644 | 19.09609 | 48.23679 |
| **Jan-26** | 33.53199 | 23.30298 | 43.761 | **Jan-27** | 33.73599 | 18.83093 | 48.64104 |
| **Feb-26** | 33.71304 | 23.05403 | 44.37204 | **Feb-27** | 33.62629 | 18.38956 | 48.86302 |
| **Mar-26** | 33.76943 | 22.6393 | 44.89902 | **Mar-27** | 33.72512 | 18.17699 | 49.27325 |

The Table represents the forecast with 95% confidence interval for Silver


Fig.2. Forecast plot using 95% confidence interval for Silver.

**IV. Conclusion:**

This study provides a comparative evaluation of ARIMA, MLP, and SVR models for forecasting precious metal prices. While ARIMA remains a foundational model for linear forecasting, its limitations are evident in dynamic, nonlinear market contexts. The MLP model leveraging deep learning structures, demonstrated superior accuracy and robustness, particularly in volatile environments. SVR also performed commendably, offering a parsimonious yet effective alternative for capturing nonlinearity with strong generalization. Across all performance metrics—RMSE, MAE, and MAPE—MLP and SVR models consistently surpassed ARIMA, affirming the value of integrating machine learning into financial forecasting. Future work may involve hybrid

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ensemble approaches, integration of exogenous macroeconomic indicators, and the application of more sophisticated deep learning architectures such as LSTM or Transformer models to further enhance forecast precision in financial time series analysis.

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